

# Identifying Risk Factors of Diabetes using Fuzzy Inference System

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## ABSTRACT

Identification of the real risk factors of diabetes is still very much inconclusive. In this paper, fuzzy rules based system was devised to identify risk factors of diabetes. The system consists of five input variables: Body Mass Index, age, blood pressure, Creatinine, and serum cholesterol and one output variable: level of risk. Three Gaussian membership functions for linguistic terms are defined for each input variable. The level of risk is defined using three triangular membership functions to represent output variable. Based on the information from patients' clinical audit reports, the system was used to classify the level of risk of fifty patients that currently undergoing regular diagnosis for diabetes treatment. The system successfully classified the risk into three levels of Low, Medium and High where three main contributing factors toward developing diabetes were identified. The three risk factors are age, blood pressure and serum cholesterol. The multi-input system that characterised by IF-THEN fuzzy rules provide easily interpretable result for identifying predictors of diabetes. Research to establish reproducibility and validity of the findings are left for future works.

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## 1. INTRODUCTION

One of the most many feared diseases that prevalent in today's lifestyle is diabetes. Diabetes is a disease where blood glucose or blood level is too high [1]. It is caused by glucose comes from the food that had been eaten. This disease has become a problem not only to the people in developed countries, but also to the people in developing and underdeveloped countries. It is a problem for all people across the globe, regardless status of development of a country [2]. There are several factors that normally linked to the development of diabetes. High blood pressure is one of the much talked factors. Adhikari et al, [3] pointed out that high blood pressure in the body can be the factor that cause diabetes in a person. In addition, there should be a difference between a diabetic person and a normal person in terms of their chronological age. People with age of more than forty years old are some of the candidates to be diagnosed with diabetes [4]. Obesity is another factor that can be associated with diabetes. The person with the problem of obesity, which is overweight can be diagnosed with diabetes. At micro level inspection, low serum creatinine is a factor of type-2 diabetes in Caucasian morbidly obese patients that is independent of age, gender, family history of diabetes, anthropometric measures, hypertension, and current smoking. Rai and Jeganathan [5-7] indicate that the person that have a higher total amount of serum cholesterol is a person that have a diabetic condition whether with or without hypertension problem. There are also other factors that can lead to diabetes, such as genetic inheritance or family history [8]. Despite a long list of factors that associated with diabetes, there has

been no solid agreement on what factors are more important than the other. Until now, many risk factors have been suggested, but the identification of a definitive authentic factor is very much inconclusive.

Many research have been conducted to investigate the relationships between factors and risk of developing diabetes. Yukako et al., [9] for example, examine the association between lifestyle and risk for diabetes among Japanese using Cox proportional hazards regression models. These data indicate that the factor of healthy behaviors prevents the incidence of diabetes. In this study, a multivariate prediction analysis of regression model is employed where large numbers of respondents involved. Bener et al., [10] examine the relationship between blood lead levels, blood pressure and diabetes as well as other selected social and biochemical factors, among workers in the United Arab Emirates. This comparative study used descriptive statistics median and geometric mean to observe the differences between two groups of respondents. The study supports the hypothesis of a positive association between lead exposure, high blood pressure and risk of diabetes and heart disease. In another related study, Fukuoka et al., [11] explore the perceived risk for diabetes and heart attack and associated health status of Caucasian, Filipino, Korean, and Latino Americans without diabetes. A cross-sectional survey approach was conducted among urban adults using descriptive statistics. They found out that older age, physical inactivity, smoking, and low HDL levels were not associated with risk of diabetes. Most of these types of research have tended to focus on statistical approaches where number of respondents were normally large and distributions of data were assumed to be normal. However, in many cases, these risk factors sometimes come with incomplete and vague information. Physical activity, for example, is difficult to express in exact measurement due to incomplete information and other intangible matters. In this sense, it is more appropriate to introduce qualitative and intelligent evaluation. Differently from previous research where statistical approaches were mainly applied, this paper aims to identify the key factors that contribute to the development of diabetes using fuzzy inference system (FIS). FIS is one example of the intelligent evaluation systems where logic-based rules are the main engine of the system. Within the architecture of FIS, factors that normally associated with the development of diabetes are defined as input variables while level of risk of diabetes is defined as output variable.

Various applications of the systems to medical diagnosis have been conducted. These applications can be very helpful to achieve classification task, offline process simulation and diagnosis, online decision support tools and process tools. Ibrahim et al., [12] for example, built a classification model using fuzzy logic classifiers. Partitioning of membership functions in a fuzzy logic inference system has been proposed. A clustering method partitions based on similarity are defined into equal clusters. Lai et al., [13] proposed a system based on FIS to measure physiological parameters continuously to provide hypoglycaemia detection for Type 1 diabetes mellitus patients. The heart rate, corrected interval of the electrocardiogram signal were among the input of the system that used to detect the hypoglycaemic episodes. An intelligent optimiser is designed to optimise the FIS parameters that govern the membership functions and the fuzzy rules. Singla [14] develops a performance comparison between Mamdani-type and Sugeno-type fuzzy models of FIS for diagnosis of diabetes. The FIS that optimized with Genetic Algorithm was used by Moallem, et al., [15] for face detection. Khanale & Ambilwade[16] presented a FIS that diagnose the thyroid diseases. De Paula Castanho [17] proposes a fuzzy system to predict pathological stage of prostate cancer. Banerjee et al., [18] apply the method based on fuzzy rules to diagnose patients with oral precancers where fuzzy rules through If-Then were utilised. The vast applications of FIS to medical diagnosis undeniably add strong evidences on the significant roles of FIS in diagnosing diseases. This study extends such advantages of inferences based system to a case of diagnosing diabetic patients.

## 2. A BRIEF OF FUZZY INFERENCE SYSTEM

Fuzzy inference system (FIS) is the process of formulating the mapping from a given input to an output using fuzzy logic operators and fuzzy rules [19]. The mapping, then provides a basis from which decisions can be made, or pattern can be identified. FIS is one of the most famous applications of fuzzy logic and fuzzy set theory [20]. In fuzzy set theory, a variable that has a value is called linguistic variable [21]. The system mainly characterised by membership functions of input and output linguistic variables, fuzzy logic operators 'or' and 'and', and if-then rules. The optimality of the output variables depends on the types of fuzzy sets used in defining input variables and also the configuration of fuzzy rules. The strength of FIS is based on their twofold identity of input and output variables which they are able to handle linguistic concepts. Based on this strength, FIS have become universal approximators that able to perform non-linear mappings between inputs and outputs. These two strengths of FIS have been used to design two types of FIS which is the Mamdani-type and Sugeno-type. The main components of the system are fuzzification interface, inference engine and defuzzification.

The basic architecture of FIS that comprises three components and rules can be seen in Figure 1.

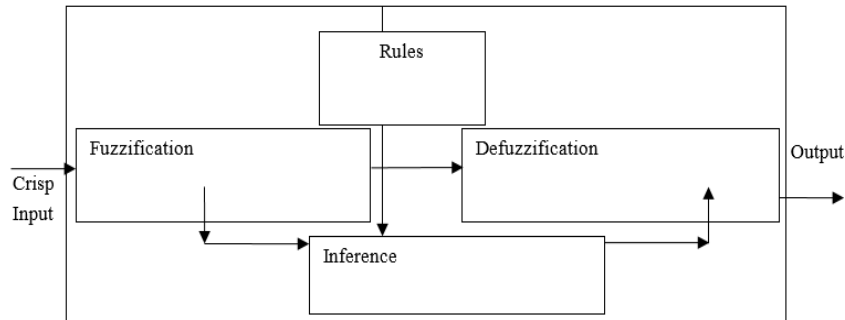


Figure 1. Basic architecture of a fuzzy inference system

The two inferences Mamdani-type and Sugeno-type are basically run in accordance with the architecture in Figure 1 where fuzzification and defuzzification are the two main processes. The third process is inference process. In Mamdani inference process, the output is defined as membership function where as, in Sugeno inference process, the output is explained by a single polynomial with respect to input variables. The Mamdani inference has a common structure with different rule bases for input and output.

The main feature of Mamdani inference is membership functions for input and input data. FIS can be envisioned as a processing tool based on the knowledge that activate to the system. The knowledge base provides membership functions and fuzzy rules needed for the process. There are five most common shapes of membership functions that can be utilised in the system: Triangular, Trapezoidal, Gaussian, Generalised-Bell, and Sigmoidal [22, 23]. The membership values of these functions can take a value from a closed interval [0,1] regardless of shapes of membership functions. For inference rules, the most common way writing fuzzy rule is given as follows.

IF premise (antecedent), THEN conclusion (consequent).

This form of rule is commonly referred to as IF-THEN rule-based system. In the case of input more than one, then multiple conjunctive antecedents 'AND' or 'OR' can be represented. For example, if we have three inputs and one output, then the rule can be written as,

IF(  $x_1$  is  $X_1$  AND  $x_2$  is  $X_2$  AND  $x_3$  is  $X_3$  ), THEN  $y_1$  is  $Y_1$ , where  $x_1$ ,  $x_2$ , and  $x_3$  are input variables,  $X_1$ ,  $X_2$ , and  $X_3$  are its respective membership functions. The output variable is represented by  $y_1$  and  $Y_1$  is the membership function of the output variable.

During the processing stage, numerical crisp variables are the input of the system. These variables are passed through a fuzzification stage where they are transformed to linguistic variables, which later become the fuzzy input for the inference engine. The fuzzy input is transformed by the rules of the inference engine to fuzzy output. These linguistic results are then changed by defuzzification stage into numerical values that become the output of the system [24]. The defuzzification technique that commonly used is center of mass where one crisp number can be obtained. It is computed using the following equation,

$$z = \frac{\sum_{j=1}^q Z_j u_c(Z_j)}{\sum_{j=1}^q u_c(z_j)}$$

where  $z$  is centre of mass and  $u_c$  is membership in class  $c$  at value  $z_j$ .

The centre of mass  $z$ , is a crisp value where interpretation of the output is straightforward. The whole research framework that explain the research protocol and method are presented in the next section.

### 3. RESEARCH FRAMEWORK

The research framework is presented to aid in conceptualizing how the input variables interact with the risks of diabetic patients. Data were retrieved from the diabetes clinical audit report of fifty patients with diabetes at a government funded hospital in the state of Selangor Malaysia after obtaining permission from the hospital authority. The clinical audit report contains information about factors that affects the development of diabetes. Body mass index (BMI), age, blood pressure, Creatinine and serum cholesterol are among the information that can be captured from the report.

The system described in Section 2 is used to translate the linguistic terms of the input variables using the IF-THEN rules and aggregate the output into crisp values. The system is expected to be able to identify the influential factors contributing to the development of diabetes. Summarily, the research framework can be depicted in Figure 2.

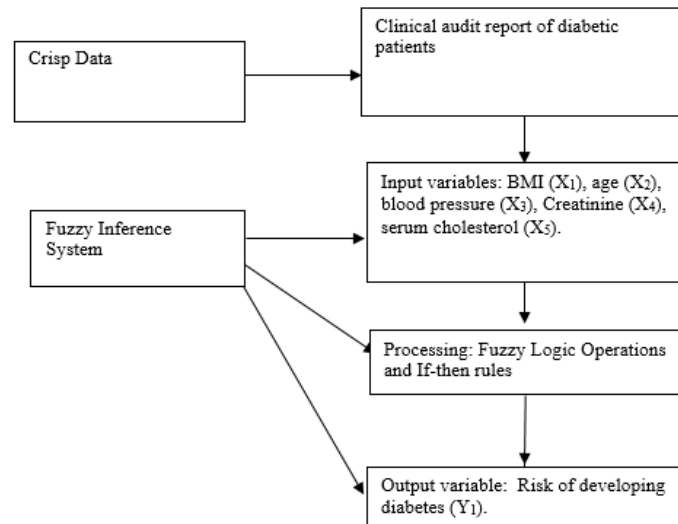


Figure 2. Framework of the research

The following section presents the results obtained from the computation of FIS over the factors that affect the diabetic patients. The full computation of the input data is implemented in the next section.

#### 4. IMPLEMENTATION AND RESULTS

Fuzzy inference system takes input, applies fuzzy rules, and produces explicit output. FIS of Mamdani inference method is suitable for identifying factors of diabetes as both the input and the output of FIS are represented by the values of linguistic variables. Detailed computations of the case can be summarised in the following steps.

##### Step 1: Defining Input and Output Variables

The five input variables are BMI, age, blood pressure, Creatinine, and serum cholesterol, which are translated into descriptive words or linguistic scales. The five input variables are then connected to the system which is Mamdani type and linked to the output, which is the level of risk of developing diabetes. Levels of the risks are measured based on the five risk factors of developing diabetes. Based on the defined system functional and operational characteristics, input crisp data from this experiment are needed to fuzzify.

##### Step 2: Defining Fuzzy Sets for System Variables

System variables need to fuzzify in order to obtain fuzzy membership values. The system recognizes the input and output variables and defines its memberships. The Gaussian membership function is utilised to define the five input variables where as the triangular membership function is utilised to defined the level of risk or output variables. Memberships for the risks of diabetes, for example, are defined in three linguistic terms, 'High', 'Medium' and 'Low'. Ranges of data are given in open interval and closed interval for input variables and output variable respectively. The open and closed intervals are defined in accordance with the type of membership functions used. Descriptions of variables, linguistic scales and ranges of crisp data in membership functions are summarised in Table 1.

The crisp value of each variable is inserted into FIS editor. For example, Figure 3 shows the range of crisp values for the variable BMI that defined in accordance with Gaussian membership function. This function is also known as normal distribution function.

Table 1. Descriptions of variables

Variables	Linguistic terms	Crisp values of membership functions given in interval
BMI (kg/m <sup>2</sup> ) $X_1$	Low	(17.8, 29.4)
	Medium	(18, 41)
	High	(29.4, 42)
Age (year) $X_2$	Adult	(32, 49)
	Old	(40, 60)
	Very Old	(50, 66)
Systolic Blood Pressure (mmHg) $X_3$	Low	(90, 120)
	Normal	(100, 145)
	High	(140, 167)
Cratinine ( $\mu\text{mol/l}$ ) $X_4$	Low	(57, 93.5)
	Normal	(60, 120)
	High	(110, 130)
Serum cholesterol (mmol/L) $X_5$	Low	(1.036, 2.5)
	Normal	(1.058, 6.55)
	High	(5.5, 9.6)
Risk of diabetes $Y_1$	Low	[0.1, 0.39]
	Normal	[0.40, 0.60]
	High	[0.61, 0.99]

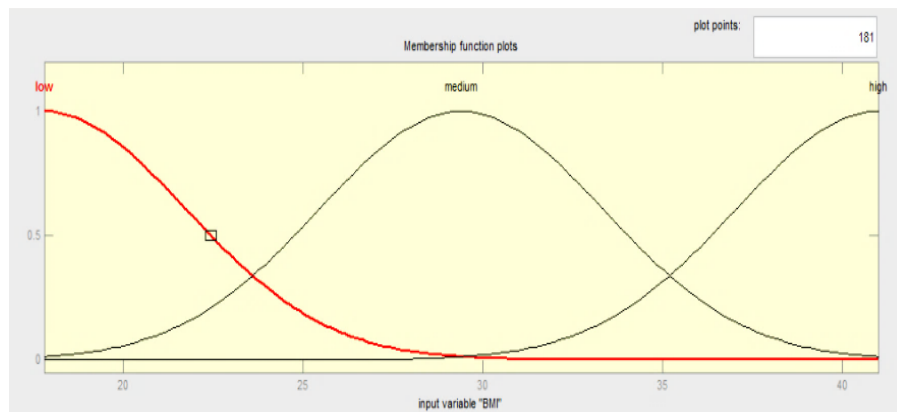


Figure 3. Input membership function for BMI

The input variable range is set to the minimum and maximum value of the data obtained from the clinical audit report. The linguistic values are {low, medium, high}.

Similarly, the output variable is defined. Unlike the input variables, the output variable utilised triangular membership function. The risks of developing obesity are assumed to be linear function that can be characterised by two right angle triangles and an equidistant triangle. Triangular fuzzy sets provide a satisfaction of a zero-error reconstruction criterion for the output interface [25]. The crisp values for output variable is shown in Figure 4.

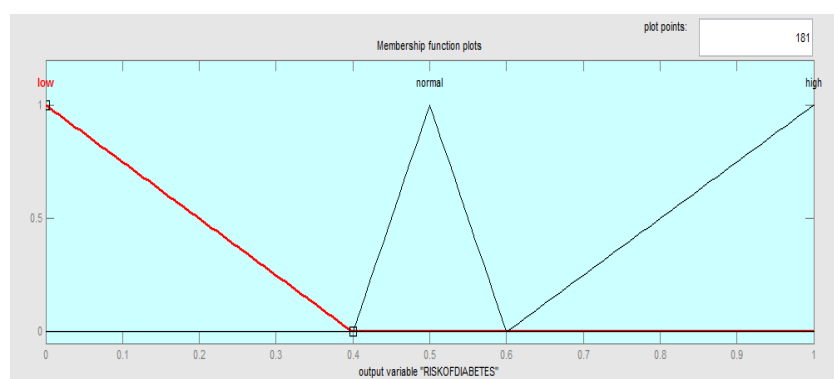


Figure 4. Output membership function

The crisp value of the output variable has been set to an interval of linguistic values {low, medium, high}.

#### Step 3: Creating rules

The next step is creating IF-THEN rules to describe the behavior of the system. The rules are designed with the purpose to describe the importance of the factors over the possibility of risks. For example, the rule created specifically for patient 1 is given as follows.

*If BMI is medium and age is adult, and blood pressure is normal and creatinine is low, and serum cholesterol is low, then risk diabetes is normal.*

According to grid partitioning, there are  $3^5 = 243$  possible rules could be generated since there are three linguistic variables and five input variables. However, based on the knowledge of a medical expert in diabetes, there are fifty rules created to describe the relationship between input variables and risk of diabetes. Figure 5 shows a sample of the rules.

1. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is low) and (SERUMCHOLESTROL is low) then (RISKOFDIABETES is normal) (1)
2. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is high) and (CREATININE is high) and (SERUMCHOLESTROL is low) then (RISKOFDIABETES is normal) (1)
3. If (BMI is low) and (AGE is adult) and (BLOODPRESSURE is high) and (CREATININE is high) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)
4. If (BMI is low) and (AGE is adult) and (BLOODPRESSURE is high) and (CREATININE is high) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)
5. If (BMI is low) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is low) and (SERUMCHOLESTROL is low) then (RISKOFDIABETES is high) (1)
6. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is high) and (CREATININE is low) and (SERUMCHOLESTROL is low) then (RISKOFDIABETES is high) (1)
7. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is high) and (CREATININE is normal) and (SERUMCHOLESTROL is low) then (RISKOFDIABETES is high) (1)
8. If (BMI is high) and (AGE is adult) and (BLOODPRESSURE is high) and (CREATININE is normal) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)
9. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is normal) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)
10. If (BMI is low) and (AGE is adult) and (BLOODPRESSURE is low) and (CREATININE is normal) and (SERUMCHOLESTROL is low) then (RISKOFDIABETES is normal) (1)
11. If (BMI is low) and (AGE is adult) and (BLOODPRESSURE is low) and (CREATININE is low) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is high) (1)
12. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is normal) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)
13. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is high) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)
14. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is high) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is low) (1)
15. If (BMI is high) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is normal) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)
16. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is low) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is high) (1)
17. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is normal) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)
18. If (BMI is high) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is low) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)
19. If (BMI is low) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is low) and (SERUMCHOLESTROL is high) then (RISKOFDIABETES is high) (1)
20. If (BMI is medium) and (AGE is adult) and (BLOODPRESSURE is normal) and (CREATININE is low) and (SERUMCHOLESTROL is high) then (RISKOFDIABETES is high) (1)
21. If (BMI is low) and (AGE is adult) and (BLOODPRESSURE is high) and (CREATININE is normal) and (SERUMCHOLESTROL is normal) then (RISKOFDIABETES is normal) (1)

Figure 5. Fuzzy rules for input and output

The inference rules set the premises to create output. The output, then need to defuzzify in order to obtain crisp value.

#### Step 4: Defuzzification

Defuzzification step is needed to convert all input data into three linguistic terms that can be used to observe the risk of diabetes. The defuzzification process transforms the fuzzy set into a crisp value that is meaningful to the end-user. For example, if a patient's BMI is 29.4, age is 49, blood pressure is 134, creatinine is 93.5, serum cholesterol is 6.55, then the defuzzification result shows the output is 0.5. Thus, based on the defined output, the level of risk is 'normal'. Defuzzification for the rest of patients was implemented with the similar fashion. A sample of the defuzzification process is shown in Figure 6.

Risks of diabetes in three levels are finally obtained after completing the defuzzification process. The risks of Low, Normal and High are described in frequency analyses for each input variable (factors). This explains the level of risk based on the number of rules in which dominant rules for factors could be identified. For example, 58 percent of BMI contributed to Medium risk of diabetes. Table 2 shows the number of rules and percentages that can be related to each level of risk.

Table 2. Number of rules and percentage based on level of risk and factors

Linguistic of risk	BMI (%)	Age (%)	Blood Pressure (%)	Creatinine (%)	Serum Cholesterol (%)
Low	17 (34)	0 (0)	6 (12)	24 (48)	20 (40)
Medium	29 (58)	3 (6)	16 (32)	20 (40)	3(6)
High	4 (8)	47 (94)	28(56)	6 (12)	27 (54)
Total	50(100)	50 (100)	50 (100)	50 (100)	50 (100)

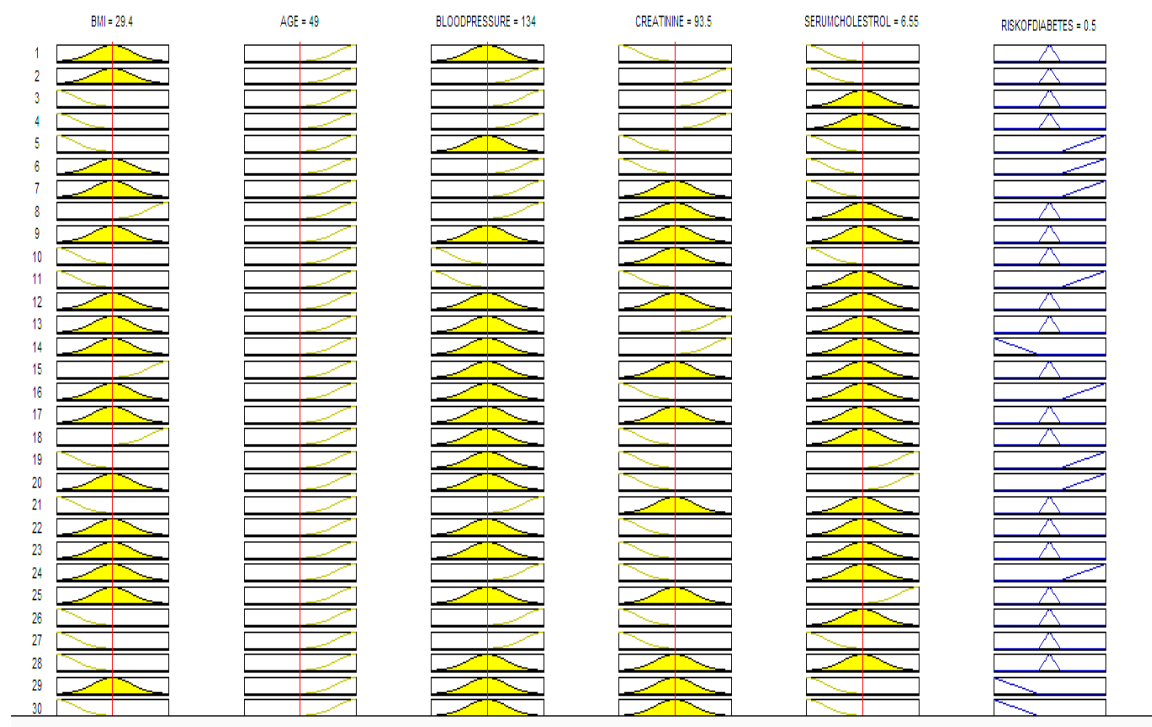


Figure 6. Defuzzification process from input to output

It can be seen that the risk of diabetes is Low if the patient has higher in creatinine. The patient is at High risk if serum cholesterol, blood pressure and age are also high. This finding concludes the three highest contributing factors toward diabetes are age, blood pressure and serum cholesterol.

The next analysis attempts to add more on the association between risk of diabetes and its related factors. From the defuzzification viewer, relationships between input and output can be visualised through a graphical modelling. The relationship shows a three-dimensional curve that represents the mapping of the membership function. It allows us to see the output surface for the two inputs [16]. Figure 7 shows the surface viewer diagram for the combination of the input of age and blood pressure.

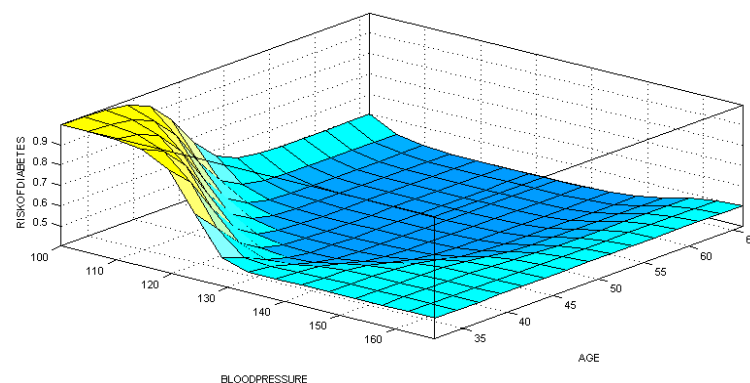


Figure 7. Relationship between age and blood pressure against risk of of diabetes

The surface explains that the risk is low when the blood pressure is in the range [110, 150] despite increases in age. It is indicated by the dark blue surface area.

The relationship between blood pressure and serum cholesterol against the risk of diabetes can be viewed in Figure 8.

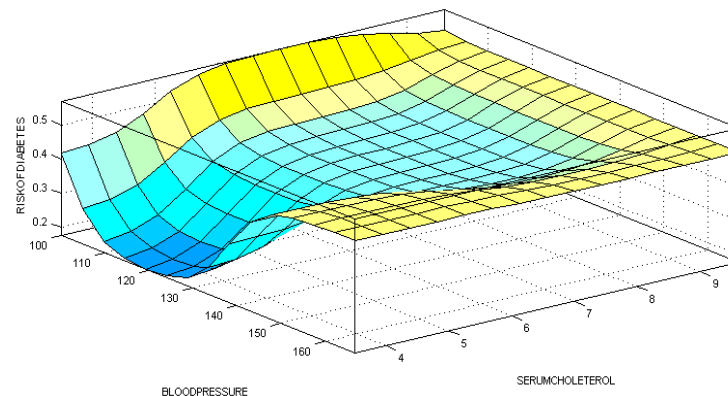


Figure 8. Relationship between serum cholesterol and blood pressure against risk of diabetes

The surface shows uneven curves which indicate that the risk of diabetes is higher when blood pressure is also getting higher despite consistency in serum cholesterol readings. In other words, the three dimensional surface also indicate low risk of diabetes if the blood pressure readings are in the range [110, 130] with low serum cholesterol. Three dimensional surface viewer diagram of the relationships of other risk factors can also be displayed with the similar way. However, these relationships diagrams are limited to the interactions between the two risk factors and level of risks.

## 5. CONCLUSION

The fuzzy inference system is a model with well-defined input and output along with a processing module that carries out all the computation at the linguistic level. It also can model the qualitative aspects of human knowledge and reasoning process without employing precise quantitative analyses. This paper has shown the superiority of fuzzy inference system for elucidating the association between risk level of diabetes and the risk factors using the rules IF-THEN in the architecture input variables, rules inferences engine and output variable. Data available from fifty clinical reports of patients with diabetes were used to identify risk factors of diabetes. Linguistic terms of five input variables and three linguistic terms of single output of risk were defined in the architecture. The carefully defined fifty rules were employed to connect the input and output. This study contributes two main findings out of the use of FIS. The system identified three most risk factors are age, blood pressure and serum cholesterol. The system also can suggest the level of risk based on interactions of two factors. These data indicate that risk of getting diabetes is higher when age, blood pressure and serum cholesterol are also higher. The system permits fuzzy rules to become a useful tool for identifying risk factors of diabetes of different groups of ages, BMI, blood pressure, creatinine and serum cholesterol.

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